A neural network algorithm for forecasting steel price in Iran

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Abstract: This study presents Artificial Neural Network (ANN) for forecasting monthly steel price based on standard economic indicators. The standard indicators used in this paper are exchange rate, import, export, gross domestic production (GDP), oil price and overall price level (OPL). First, an ANN approach is illustrated based on supervised multi layer perceptron (MLP) network for the steel price forecasting. The chosen model therefore can be compared to that of estimated by fuzzy regression (FR) and conventional regression models. Seven FR models are considered in this research and each of these models has different approach and advantages. The lowest Mean Absolute Percentage Error (MAPE) value is used to select the best model. To show the applicability and superiority of the ANN the data for monthly steel price in Iran from 2008 to 2011 (48 months) is used. The results show that the ANN provides accurate solution for steel price estimation problem.
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1. Introduction

Steel products are among the most important intermediate products in the world today. Steel production is an important indicator for judging the industrialization level of a country. The analysis of the determination of steel prices is of great practical importance, particularly for the formulation of economic policy in less-developed country. In this study an Artificial Neural Network (ANN) approach is illustrated based on supervised multi layer perceptron (MLP) network for the steel price forecasting. The chosen model therefore can be compared to that of estimated by fuzzy regression and conventional regression model. The estimation of steel price based on economic and non-economic indicators may be achieved by certain linear or non-linear statistical, mathematical and simulation models. Due to the fluctuations of steel price, the non-linear forms of the equations could estimate steel price more effectively. The non-linearity of these indicators has lead to search for intelligent solution approach methods such as genetic algorithms (GA), fuzzy regression and ANN. The ANN have been used in nonlinear modeling and forecasting. Several studies have been conducted on the application of artificial intelligence techniques to forecasting problem (Yalcinoz and Eminoglu, 2005, Hsu and Chen, 2003, Beccali et al, 2004, Khotanzad et al, 1995, Khotanzad et al, 1996, Chow and Leung, 1996, Hobbs et al, 1998, Lee and Park, 1992, Mohammed et al, 1995, Yalcinoz and Eminoglu, 2005, Azadeh et al, 2006b, 2006c, 2007). This is because of the ANN's ability to learn and construct a complex nonlinear mapping through a set of input/output examples.

Regression analysis refers to a set of methods by which estimates are made for the model parameters from the knowledge of the values of a given input-output data set. The goals of the regression analysis are finding an appropriate mathematical model, and determining the best fitting coefficients of the model from the given data. The use of statistical regression is bounded by some strict assumptions about the given data. Overcoming such limitations, fuzzy regression (FR) is introduced which is an extension of the classical regression and is used in estimating the relationships among variables where the available data are very limited and imprecise and variables are interacting in an uncertain, qualitative and fuzzy way (Azadeh et al, 2008a). FR models have been successfully applied to various problems such as forecasting (Wang and Tsaur, 2000) and engineering (Lai and Chang, 1994). It can also be applied for steel prices forecasting problems.

The remainder of this paper is organized as follows: In Section 2, fundamental factors influencing the price of steel products is described. ANN model is described in Section 3. In Section 4 FR models and in Section 5 obtained results of the case study are presented. At last in Section 7 the conclusions of this study are presented.

2. Fundamental factors influencing the price of steel products

Richardson (1998, 1999) evaluates fundamental factors such as exchange rate, cost structure, demand, technology *and* state aids that influencing the price of steel products. Jiang Xia (2000) introduce exchange rate, overall price level (OPL), economic growth (gross national product), imports and exports as fundamental factors that influencing the price of steel products. The standard indicators used in this paper are exchange rate, import, export, gross domestic production (GDP), oil price and overall price level (OPL).

3.1 Overall price level

The economy's price level is the price of a broad reference basket of goods and services. A rapidly developing national economy increases market demand and makes prices rise. The rise of industrial product prices forms a cost-push effect on the general price level. If the overall price level rises, individual households and firms must spend more money than before to purchase their usual weekly market baskets of goods and services. As a result commodity prices increase too. There is a positive relationship between the overall price level and the price of steel products. This relationship occurs because the price of steel products rises with an increase in costs when commodity prices rise and with the excess demand for steel products (Xia J, 2000).

3.2 Economic growth **(**gross domestic production**)**

Economic growth is the expansion of the economy's production possibilities. The gross domestic production (GDP) is among the most important social statistics for a society. GDP is a summary measure of total output in an economy and is often used as a measure of social welfare. It has been used to develop aggregate productivity measures in economic development and is often an important determinant of demand for the products of individual firms. Economic growth is measured by the increase in real gross domestic product. We are interested in economic growth because to some extent it offers us the explanation of steel prices from the demand side. Different levels of economic development cause different demands for commodities. Developed countries all experience high demand for steel products. Developed countries all experience high demand for steel products. In the middle stage of development when a economy takes off, the scale of fixed asset investment is large, consumption of steel products is high, demand for steel products is at a high level, however, increases in supply is relatively slow, customs duties are high, prices and profit rates are relatively high. After a country enters into a mature industrialization stage, demand for steel products is no longer at its peak and excess production capacity often exists in the industry. More attention is paid to optimization of product structure with an increase in the production of upgraded products with high additional value. So the domestic price decreases and the steel industry has only minimal profit (Xia J, 2000). There is a positive relationship between the GNP and the price of steel products. The increases in GNP will raise the demand for steel products, which increases the prices of steel products.

3.3 Exchange rate

The exchange rate for a currency is its price in the terms of another currency. Households and firms use exchange rates to translate foreign prices into domestic currency terms. Once the prices of domestic goods and imports have been expressed in terms of the domestic currency, household and firms can compute the relative prices that affect international trade flows. Furthermore, steel product prices could also be affected by changes in the exchange rate of other related countries. Because we are in a world-wide economy it is obvious that other countries' economic status could affect our own country (Xia J, 2000).

3.4 Imports and Exports

The economies of all nations are linked to one another through a complex network of trade and financial relationships. International trade is an important element in virtually every economy. In some nations it may represent as much as one-fourth of the total national product. When one country imports products, these imports enter the economy to compete in markets with domestically produced goods. The domestic price of the product will tend to fall, and profit, as well as volume of sales, is likely to suffer. Therefore, output and employment in this import-competing industry are likely to fall. While output and employment fall in the import-related industry, the supply of steel products increases which results in decreases in the price of steel products. Consequently, output and employment tend to rise in the exporting industries of the country, as the money that is used to pay for imports eventually is funneled back into the country for investment or for the acquisition of products and services. The domestic price of steel products will tend to rise (Xia J, 2000). The increase of exports will result in a decrease in the quantities of supply in the domestic market, which results in an increase in the domestic price in steel products and on the contrary imports are associated with lower domestic prices.

3.5 *Cost structure*

The cost structure of steel production is such that high operation rates are vital for survival and firms aim for high operation rates, if only to sell the excess output overseas. Prices for such exports may, therefore, depend entirely on what the market will bear. Cost structure composed of scrap price, coal price, wage, oil price and so on. In this article, oil price that influence factory and transportation cost select as major part of cost structure (Xia J, 2000).

4. Artificial Neural Networks

ANNs consists of an inter-connection of a number of neurons. There are many varieties of connections under study, however here we will discuss only one type of network which is called the Multi Layer Perceptron (MLP). In this network the data flows forward to the output continuously without any feedback. The input nodes are the previous lagged observations while the output provides the forecast for the future value. Hidden nodes with appropriate nonlinear transfer functions are used to process the information received by the input nodes. The model can be written as:

$$y_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-i} + \beta_{0j} \right) + \varepsilon_t \qquad (1)$$

Where m is the number of input nodes, n is the number of hidden nodes, f is a sigmoid transfer function such as the logistic: $f(x) = \frac{1}{1+\exp(-x)}$. $\{\alpha_j,\ j = 0, 1,..., n\}$ is a vector of weights from the hidden to output nodes and $\{\beta_{ij},\ i = 1, 2,…, m;\ j = 0, 1,…, n\}$ are weights from the input to hidden nodes. α_0 and β_{oj} are weights of arcs leading from the bias terms which have values always equal to 1. Note that Equation (1) indicates a linear transfer function is employed in the output node as desired for forecasting problems. The MLP's most popular learning rule is the error back propagation algorithm. Back Propagation learning is a kind of supervised learning introduced by Werbos (Werbos, 1974) and later developed by Rumelhart and McClelland (Rumelhart and McClelland, 1986). At the beginning of the learning stage all weights in the network are initialized to small random values. The algorithm uses a learning set, which consists of input – desired output pattern pairs. Each input – output pair is obtained by the offline processing of historical data. These pairs are used to adjust the weights in the network to minimize the Sum Squared Error (SSE) which measures the difference between the real and the desired values overall output neurons and all learning patterns. After computing SSE, the back propagation step computes the corrections to be applied to the weights.

5. Fuzzy Regression Models

Fuzzy linear regression was introduced by Tanaka et al., (1982), to decide a fuzzy linear relationship by, $Y = A_0X_0 + A_1X_1 + \ldots + A_kX_k$; Where regression coefficients A_j, j = 0... K, were supposed to be a symmetric triangular fuzzy number, with center α_j, having membership function equal to one, and spreads c_j, $c_j \geq 0$. The dependent variable (y) is a fuzzy number. The independent variables (x) can be taken into consideration as crisp or fuzzy numbers.

The input information are n sets of variables $y_i, x_{i0}, x_{i1}, \ldots, x_{ij}$, $i = 1, 2, \ldots, n;\ n \geq j+1$, where $x_{i0} = 1$. The response variable y_i is assumed to be a symmetric triangular fuzzy number with central value $\bar{y}_i$ and spreads $\bar{e}_i$, where $\bar{e}_i \geq 0$. Independent variables values x_{ij}, $i = 1, 2, \ldots, n$ $j = 1, 2, \ldots, k$, is also supposing to be a symmetric triangular fuzzy number with a center $\bar{x}_{ij}$ and spreads f_{ij} ($f_{ij} \geq 0$). The assigned membership functions of both dependent and independent variables are linear. If we are just interested in that membership function value of y_i has at least H, where $0 \leq H \leq 1$, we should consider the interval $[\bar{y}_i - (1-\mathrm{H}) \times \bar{e}_i \quad \bar{y}_i + (1-\mathrm{H}) \times \bar{e}_i]$.

Here, H shows the minimum acceptable degree of precision, and we will make reference to this interval as H-certain observed interval. Similarly, suppose that the independent variables x_j, $j = 1, 2, \ldots k$, have certain values and regression coefficient A_j, $j = 1, 2, \ldots k$, are assume to be symmetric triangular fuzzy numbers, the estimated interval corresponding to a input set of independent variables X $(x_{i0}, x_{i1}, \ldots, x_{ik})$ having membership function value of at least H is:

$$\left[\sum_{j=0}^{k} (\alpha_j - (1-H) \times c_j) \times x_{ij} \quad \sum_{j=0}^{k} (\alpha_j + (1-H) \times c_j) \times x_{ij} \right],$$

We will refer to this distance as H-certain estimated interval.

The membership function of the fuzzy parameter A_j is represented by:

$$\mu_{A_j}(a_j) = \begin{cases} 1 - \dfrac{|\alpha_j - a_j|}{c_j} & \text{for } \alpha_j - c_j \leq a_j \leq \alpha_j + c_j \\ 0 & \text{otherwise} \end{cases}$$

The formulation of FR model of Tanaka et al. (1982) is:

$$\text{Minimize} \quad \sum_{i=1}^{n}\sum_{j=0}^{k} c_j x_{ij} \tag{2}$$

$$\text{subject to:} \quad \sum_{j=0}^{k}\left(\alpha_j + (1-H)\times c_j\right)\times x_{ij} \geq \bar{y}_i + (1-H)\times \bar{e}_i \qquad i = 1,\cdots,n,$$

$$\sum_{j=0}^{k}\left(\alpha_j - (1-H)\times c_j\right)\times x_{ij} \leq \bar{y}_i - (1-H)\times \bar{e}_i \qquad i = 1,\cdots,n,$$

$$\alpha_j = \text{free}, \quad c_j \geq 0, \quad j = 0,\cdots,k.$$

Sakawa and Yano (Sakawa et al., 1992) studied Case 2. First, depending upon the presumed range of values of coefficients A_j, Sakawa and Yano would categorize the independent variables into three classes:

J_1 = those variables $j, j = 0,\cdots,k,$ which will have $\alpha_j - (1-H)\times c_j \geq 0,$
J_2 = those variables $j, j = 0,\cdots,k,$ which will have $\alpha_j - (1-H)\times c_j < 0,$ and $\alpha_j + (1-H)\times c_j \geq 0,$
J_3 = those variables $j, j = 0,\cdots,k,$ which will have $\alpha_j + (1-H)\times c_j < 0.$

Then, the FR model of this approach will be formulated as follows:

$$\text{Minimize} \quad \sum_{i=1}^{n}\left(\hat{y}_{iU} - \hat{y}_{iL}\right) \tag{3}$$

$$\text{subject to:} \quad \sum_{j\in J_1\cup J_2}\left(\alpha_j + (1-H)\times c_j\right)\times\left(\bar{x}_{ij} + (1-H)\times f_{ij}\right) + \sum_{j\in J_3}\left(\alpha_j + (1-H)\times c_j\right)\times\left(\bar{x}_{ij} - (1-H)\times f_{ij}\right) = \hat{y}_{iU},$$

$$i = 1,\cdots,n,$$

$$\hat{y}_{iU} \geq \bar{y}_i - (1-H)\times \bar{e}_i, \quad i = 1,\cdots,n,$$

$$\sum_{j\in J_1}\left(\alpha_j - (1-H)\times c_j\right)\times\left(\bar{x}_{ij} - (1-H)\times f_{ij}\right) + \sum_{j\in J_2\cup J_3}\left(\alpha_j - (1-H)\times c_j\right)\times\left(\bar{x}_{ij} + (1-H)\times f_{ij}\right) = \hat{y}_{iL},$$

$$i = 1,\cdots,n,$$

$$\hat{y}_{iL} \leq \bar{y}_i + (1-H)\times \bar{e}_i, \quad i = 1,\cdots,n,$$

$$\alpha_j = \text{free}, \quad c_j \geq 0, \quad j = 0,\cdots,k.$$

Sakawa and Yano also proposed the following problem:

$$\text{Minimize} \quad \sum_{i=1}^{n}\left(\hat{y}_{iU} - \hat{y}_{iL}\right) \tag{4}$$

$$\text{subject to:} \quad \sum_{j\in J_1\cup J_2}\left(\alpha_j + (1-H)\times c_j\right)\times\left(\bar{x}_{ij} + (1-H)\times f_{ij}\right) + \sum_{j\in J_3}\left(\alpha_j + (1-H)\times c_j\right)\times\left(\bar{x}_{ij} - (1-H)\times f_{ij}\right) = \hat{y}_{iU},$$

$$i = 1,\cdots,n,$$

$$\hat{y}_{iU} \geq \bar{y}_i - H\times \bar{e}_i, \quad i = 1,\cdots,n,$$

$$\sum_{j\in J_1}\left(\alpha_j - (1-H)\times c_j\right)\times\left(\bar{x}_{ij} - (1-H)\times f_{ij}\right) + \sum_{j\in J_2\cup J_3}\left(\alpha_j - (1-H)\times c_j\right)\times\left(\bar{x}_{ij} + (1-H)\times f_{ij}\right) = \hat{y}_{iL},$$

$$i = 1,\cdots,n,$$

$$\hat{y}_{iL} \leq \bar{y}_i + H\times \bar{e}_i, \quad i = 1,\cdots,n,$$

$$\alpha_j = \text{free}, \quad c_j \geq 0, \quad j = 0,\cdots,k.$$

Attention that in the right-hand-side of in above constraints, H is applied as a substitute ($1-H$), with respect to the concept of necessity. Sakawa and Yano also introduced an interactive method to find the suitable value of H by balancing the increase in the value of H, versus the increase in the objective function's value. The models with this consideration are that (1) $\hat{y}_{iU}$ and $\hat{y}_{iL}$ are only estimation of approximated values upper and lower surface amounts, and (2) categorizing the independent values into three cases in front of performing the regression is not simple (Sakawa et al., 1992), (Hojati et al., 2005).

Peters (1994) considered Case (1). His FR model is a little complex to explain. Assume that y_{iU}, $\bar{y}_i$ and y_{iL} be the upper, center, and lower values of i^{th} observed interval, and let $\hat{y}_{iU}$ and $\hat{y}_{iL}$ be the upper and lower values of the i^{th} estimated interval. This model permits $\hat{y}_{iL}$ to be greater than y_{iL} but smaller than y_{iU}, and $\hat{y}_{iU}$ to be smaller than y_{iU} but greater than y_{iL}. In fact, the mean of all deviations of $\hat{y}_{iU}$ from $\bar{y}_i$, if $\hat{y}_{iU} < \bar{y}_i$, and $\hat{y}_{iL}$ from $\bar{y}_i$, if $\hat{y}_{iL} > \bar{y}_i$, is minimized. This objective function is balanced against the total spreads of estimated intervals equation. By changing Tanaka et al (1989) into an objective and converting it as a constraint. The formulation of Peters (1994) model is:

$$
\begin{aligned}
&\text{Maximize} \quad \bar{\lambda} \qquad\qquad (5)\\
&\text{subject to:} \quad \sum_{j=0}^{k}(\alpha_j + c_j)\times x_{ij} \ge \bar{y}_i - (1-\lambda_i)\times \bar{e}_i \qquad i = 1,\cdots,n,\\
&\sum_{j=0}^{k}(\alpha_j - c_j)\times x_{ij} \le \bar{y}_i + (1-\lambda_i)\times \bar{e}_i \qquad i = 1,\cdots,n,\\
&\bar{\lambda} = (\lambda_1 + \lambda_1 + \cdots \lambda_1)/n,\\
&\sum_{i=1}^{n}\sum_{j=0}^{k} c_j x_{ij} \le P_0 \times (1-\bar{\lambda}),\\
&0 \le \lambda_i \le 1, \quad i = 1,\cdots,n, \quad \bar{\lambda} \ge 0,\\
&\alpha_j = \text{free}, \quad c_j \ge 0, \quad j = 0,\cdots,k.
\end{aligned}
$$

It is difficult to determining a good value for P_0, and the result is sensitive to this parameter (Peters, 1994), (Hojati et al., 2005).

Ozelkan and Duckstein (2000) introduced a similar model to Peters (1994) but have not needed the estimation intervals to divide the observed intervals. The formulation of Ozelkan and Duckstein (2000) can be written as follows:

$$
\begin{aligned}
&\text{Minimize} \quad \sum_{i=1}^{n}(d_{iU} + d_{iL}) \qquad\qquad (6)\\
&\text{subject to:} \quad \sum_{j=0}^{k}(\alpha_j + (1-H)\times c_j)\times x_{ij} \ge \bar{y}_i + (1-H)\times \bar{e}_i - d_{iU} \qquad i = 1,\cdots,n,\\
&\sum_{j=0}^{k}(\alpha_j - (1-H)\times c_j)\times x_{ij} \le \bar{y}_i - (1-H)\times \bar{e}_i + d_{iL} \qquad i = 1,\cdots,n,\\
&\sum_{i=1}^{n}\sum_{j=0}^{k} c_j x_{ij} \le \upsilon,\\
&d_{iL}, d_{iU} \ge 0, \qquad i = 1,\cdots,n,\\
&\alpha_j = \text{free}, \quad c_j \ge 0, \quad j = 0,\cdots,k,
\end{aligned}
$$

Where υ is a parameter and which should be diversified over all possible amounts of total spreads of estimated intervals, and d_{iU} and d_{iL}, $i = 1..., n$, are upper and lower shift variables. Hojati et al. (2005) introduced a simple goal programming-like method to select the FR coefficients such that the total deviation of upper values of *H*-certain estimated and corresponded observed intervals and deviation of lower values of *H*-certain estimated and related observed intervals are minimized. This can be obtained by using the following formulation:

$$\begin{aligned}
&\text{Minimize} \quad \sum_{i=1}^{n}\left(d^{+}{}_{iU} + d^{-}{}_{iU} + d^{+}{}_{iL} + d^{-}{}_{iL}\right) \qquad (7)\\
&\text{subject to:} \quad \sum_{j=0}^{k}\left(\alpha_j + (1-H)\times c_j\right)\times x_{ij} - d^{-}{}_{iU} \geq \bar{y}_i + (1-H)\times \bar{e}_i - d^{+}{}_{iU} \qquad i = 1,\cdots,n,\\
&\sum_{j=0}^{k}\left(\alpha_j - (1-H)\times c_j\right)\times x_{ij} - d^{-}{}_{iL} \leq \bar{y}_i - (1-H)\times \bar{e}_i + d^{+}{}_{iL} \qquad i = 1,\cdots,n,\\
&\sum_{i=1}^{n}\sum_{j=0}^{k} c_j x_{ij} \leq \upsilon,\\
&d^{+}{}_{iU}, d^{-}{}_{iU}, d^{+}{}_{iL}, d^{-}{}_{iL} \geq 0, \qquad i = 1,\cdots,n,\\
&\alpha_j = \text{free}, \quad c_j \geq 0, \quad j = 0,\cdots,k,
\end{aligned}$$

$$\begin{aligned}
&\text{Minimize} \quad \sum_{i=1}^{n}\left(d^{+}{}_{ilU} + d^{-}{}_{ilU} + d^{+}{}_{ilL} + d^{-}{}_{ilL} + d^{+}{}_{irU} + d^{-}{}_{irU} + d^{+}{}_{irL} + d^{-}{}_{irL}\right) \qquad (8)\\
&\text{subject to:} \quad \sum_{j=0}^{l}\left(\alpha_j + (1-H)\times c_j\right)\times\left(\bar{x}_{ij} - (1-H)\times f_{ij}\right) - d^{-}{}_{ilU} = \bar{y}_i + (1-H)\times \bar{e}_i - d^{+}{}_{ilU},\\
&i = 1,\cdots,n,\\
&\sum_{j=0}^{l}\left(\alpha_j + (1-H)\times c_j\right)\times\left(\bar{x}_{ij} + (1-H)\times f_{ij}\right) - d^{-}{}_{irU} = \bar{y}_i - (1-H)\times \bar{e}_i - d^{+}{}_{irU},\\
&i = 1,\cdots,n,\\
&\sum_{j=0}^{l}\left(\alpha_j - (1-H)\times c_j\right)\times\left(\bar{x}_{ij} - (1-H)\times f_{ij}\right) - d^{-}{}_{ilL} = \bar{y}_i + (1-H)\times \bar{e}_i - d^{+}{}_{ilL},\\
&i = 1,\cdots,n,\\
&\sum_{j=0}^{l}\left(\alpha_j - (1-H)\times c_j\right)\times\left(\bar{x}_{ij} + (1-H)\times f_{ij}\right) - d^{-}{}_{irL} = \bar{y}_i - (1-H)\times \bar{e}_i - d^{+}{}_{irL},\\
&i = 1,\cdots,n,\\
&\sum_{i=1}^{n}\sum_{j=0}^{k} c_j x_{ij} \leq \upsilon,\\
&d^{+}{}_{ilU}, d^{-}{}_{ilU}, d^{+}{}_{ilL}, d^{-}{}_{ilL}, d^{+}{}_{irU}, d^{-}{}_{irU}, d^{+}{}_{irL}, d^{-}{}_{irL} \geq 0, \qquad i = 1,\cdots,n,\\
&\alpha_j = \text{free}, \quad c_j \geq 0, \quad j = 0,\cdots,k,
\end{aligned}$$

Note that for each indices $i = 1... N$, at most one of $d^{+}{}_{iU}$ or $d^{-}{}_{iU}$ and $d^{+}{}_{iL}$ or $d^{-}{}_{iL}$ would be positive. Thus the $|d^{+}{}_{iU} - d^{-}{}_{iU}|$ is the distance between upper value of *H*-certain estimation interval and the upper value of the *H*-certain observed interval, therefore the $|d^{+}{}_{iL} - d^{-}{}_{iL}|$ is the distance between lower value of *H*-certain estimated interval and the lower value of the *H*-certain observed interval. The objective is to minimize the sum of these two intervals (Hojati et al., 2005).

In Case 2, Hojati et al. (2005) select the FR coefficients so that the total difference between upper values of estimated and related observed intervals and distance among lower values of estimated and related observed intervals are minimized at both lower values and upper values of each of the independent variable. For easiness, the following model is formulated for the condition that there is only one independent variable.

Where in the indices *l* refers to the lower value and *r* refers to the upper value for the intervals of the independent variable, moreover *U* refers to the upper value and *L* refers to the lower value of the observed and estimated intervals (Hojati et al., 2005).

In this study the best model is distinguished by running and testing these various FR models and selecting the model with lowest error.

In order to estimate annual oil consumption, the $Y = A_0X_0 + \ldots + A_4X_4$ fuzzy linear relationship can be taken into consideration, where A_j s; $j = 0,1,2,3,4$ are fuzzy coefficients, Y indicates the monthly steel price, X_0 equals to one, X_1 represents the exchange rate, X_2 is the import, X_3 indicates the GDP, X_4 represents the export, X_5 is the OPL and X_6 indicates the oil price. Exchange rate, GDP, oil price and OPL are collected from the www.cbi.ir. Import and export collected from the www.tccim.ir and steel price collected from the Iran mercan tile exchange (http://ime.co.ir).

Table 1. The row data for Iran

Period	Export	Import	Economic Growth	Exchange Rate	Oil Price	Overall Price Level	Steel Price
1	134800	609000	103627	10174	31.33	238.1	4195
2	135000	608000	103627	10262	30.65	238	4118
3	135000	607520	103627	10454	33.7	238.1	3940
4	135000	607520	129426	10760	33.23	243.6	3939
5	135600	608000	129426	10782	37.71	243	4069
6	136000	609000	129426	10635	35.21	243.2	4017
7	134500	608000	116558	11035	38.33	254	3966
8	195000	607000	116558	11475	42.87	254	3605
9	202000	606000	116558	11668	43.43	254	3606
10	200000	605000	111996	11542	49.74	261	3755
11	203000	604000	111996	11570	42.8	261.2	3725
12	204000	605500	111996	11570	39.43	261.1	3750
13	239000	529000	132314	11555	44.01	266.9	3750
14	239500	530000	132314	11305	44.87	266	3750
15	181000	531000	132314	10979	52.6	266.8	3766
16	237000	530000	158122	10866	51.87	267.6	3670
17	236000	528500	158122	10936	48.9	267.6	3673
18	237000	528600	158122	10989	54.73	267.6	3689
19	182000	528600	139570	10879	57.47	272.9	3727
20	180000	527000	139570	10624	64.06	272	3943
21	180500	528000	139570	10884	62.75	271.9	3859
22	240000	528160	132630	11012	58.75	279.5	3946
23	183000	528000	132630	10873	55.41	279.4	4032
24	184000	529000	132630	11125	57.02	279.6	4366
25	148000	665000	163932	11211	63.05	288.4	4545
26	192000	666000	163932	11750	60.12	288.5	5485
27	192500	664500	163932	11551	62.08	288.6	5562
28	190000	664500	188999	11579	70.35	299.6	5717
29	192000	665200	188999	11778	69.83	299	6904
30	189000	666000	188999	12417	68.69	299	6755
31	146000	663500	169908	11668	73.66	307.4	6837
32	145500	663600	169908	11615	73.11	307	6556
33	146000	664500	169908	11841	61.71	307.4	6581
34	145600	664000	156638	11946	57.8	314.7	6850
35	190000	666000	156638	12120	58.62	314.6	7635
36	150000	665000	156638	12289	62.23	314.8	8012
37	143000	970200	194537	12289	53.78	327.3	7561
38	148000	958000	194537	12493	57.43	327.3	7416
39	146000	962000	194537	12414	62.15	327.3	7507
40	147000	960000	236522	12835	67.51	339	7467
41	145000	961000	236522	12572	67.38	339.1	7129
42	189000	958000	236522	13078	71.55	339.1	7480
43	188000	955000	231418	13287	77.01	352.8	8134
44	189500	956000	231418	13660	70.74	352.8	7828
45	146000	957000	231418	13565	76.87	352.8	7715
46	183000	958300	211916	13660	82.5	370.1	7916
47	185000	956000	211916	13727	92.62	371	7993
48	189000	960000	211916	14111	91.25	370.6	7995

The steps of studying the steel price estimation are illustrated below:

Step 1: Collection of input variables: X_1, X_2, X_3 and X_4 for a statistically robust period.

Step 2: Tuning and running all of the mentioned FR models through using train data.

Step 3: calculating the MAPE through comparing estimated steel price with their actual values in test data and select the FR model which has the lowest MAPE error as the best model.

6. Results and discussion of the case study

In this section, the result of solving ANN, FR and conventional regression will be presented. The raw data with respect to the dependent and independent variables in Iran are shown in Table 1. The data is used to identify the preferred model to forecast and estimate steel price in Iran. We chose mean absolute percentage error (MAPE) for our work that can be calculated by the following equation (9):

$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{x_t - x'}{x_t} \right|}{n} \quad (9)$$

Where x' is the estimated steel price and x_t is the actual value of steel price. As input data used for the model estimation have different scales, MAPE method is the most suitable to be used to estimate the errors. The results obtained from the ANN, FR and conventional regression are shown in Table 2, 3 and 4.

Table 2. The Mape results for neural network

test number	ANN
6	0.01414
7	0.18842
8	0.214787
9	0.209624
10	0.22306
11	0.237664
12	0.280149
13	0.258803
14	0.245517
15	0.23146
16	0.217325
17	0.201862
18	0.185609
19	0.184166
20	0.180648
21	0.172277
22	0.166716
23	0.161129
24	0.154663
mean	0.196212

Table 3. The Mape results of FR models

test number	hbs1	hbs2	ozek	peter	sak1	tanaka	min
6test	0.46566856	0.4624	0.442093	0.328396	0.542147	0.430456	0.328396269
7test	0.41302103	0.382	0.347273	0.222974	0.482957	0.394078	0.222974153
8test	0.34631366	0.341	0.351081	0.49363	0.38352	0.368558	0.341002324
9test	0.26174346	0.3004	0.338141	0.350931	0.352079	0.343698	0.261743463
10test	0.27156715	0.2716	0.302815	0.318808	0.331054	0.305779	0.271567146
11test	0.30063566	0.3006	0.302206	0.309245	0.312651	0.167506	0.167506288
12test	0.75005006	0.2104	0.372308	0.752928	0.303847	0.607251	0.21039564
13test	0.72587734	0.8638	0.944115	0.956727	0.28723	0.486335	0.287230155
14test	0.72511568	0.8615	0.706874	0.460594	0.273121	0.487906	0.273120932
15test	0.70316452	0.8664	0.943917	0.837717	0.259888	0.239438	0.239437802
16test	0.72026309	0.8421	0.235773	0.893039	0.249085	0.490854	0.2357725
17test	0.72066272	0.7666	0.887	0.9892	0.240044	0.491844	0.240044061
18test	0.72391464	0.7633	0.320582	0.596001	0.231189	0.492723	0.231188828
19test	0.72511695	0.8358	0.355748	0.977127	0.221985	0.494846	0.221985181
20test	0.72587698	0.896	0.207225	0.647891	0.21201	0.496762	0.207224824
21test	0.74332	0.9029	0.954333	0.755621	0.20209	0.498532	0.202089561
22test	0.74625908	0.9023	0.94951	0.928323	0.196244	0.480351	0.196244235
23test	0.55442231	0.8904	0.220522	0.884037	0.195049	0.47083	0.195048636
24test	0.40011857	0.7071	0.729734	0.910584	0.207541	0.146739	0.146739347
mean	0.58016376	0.6509	0.521645	0.663883	0.288617	0.415499	0.235774281

Table 4. The mape result of conventional regression

test number	conventional regression
6	0.476645
7	0.42983
8	0.300904
9	0.266934
10	0.415599
11	0.584556
12	0.379595
13	0.382705
14	0.373285
15	0.384387
16	0.354048
17	0.36924
18	0.400272
19	0.395964
20	0.392987
21	0.318185
22	0.311224
23	0.323368
24	0.191523
mean	0.371118

As mentioned, these results were derived from 6, 7,…, 23 and 24 rows of unlearned data. The MAPE results of FR models and comparison are shown in Chart 1.

With compare result of ANN, FR and conventional regression it can be seen that neural network get less error than fuzzy regression and conventional regression. It shown in Table 5 and Chart 2.

Table 5. The best result of any period in various method

test number	ANN	fuzzy regression	conventional regression
6	select		
7	select		
8	select		
9	select		
10	select		
11		select	
12		select	
13	select		
14	select		
15	select		
16	select		
17	select		
18	select		
19	select		
20	select		
21	select		
22	select		
23	select		
24		select	

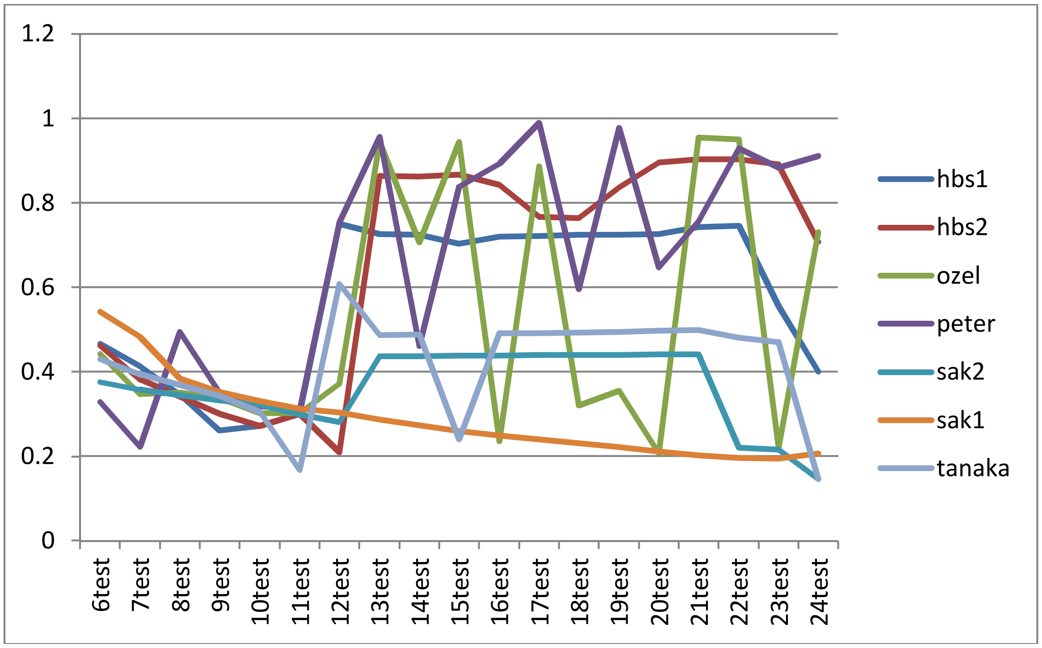

Chart 1. Comparision of fuzzy regression models.

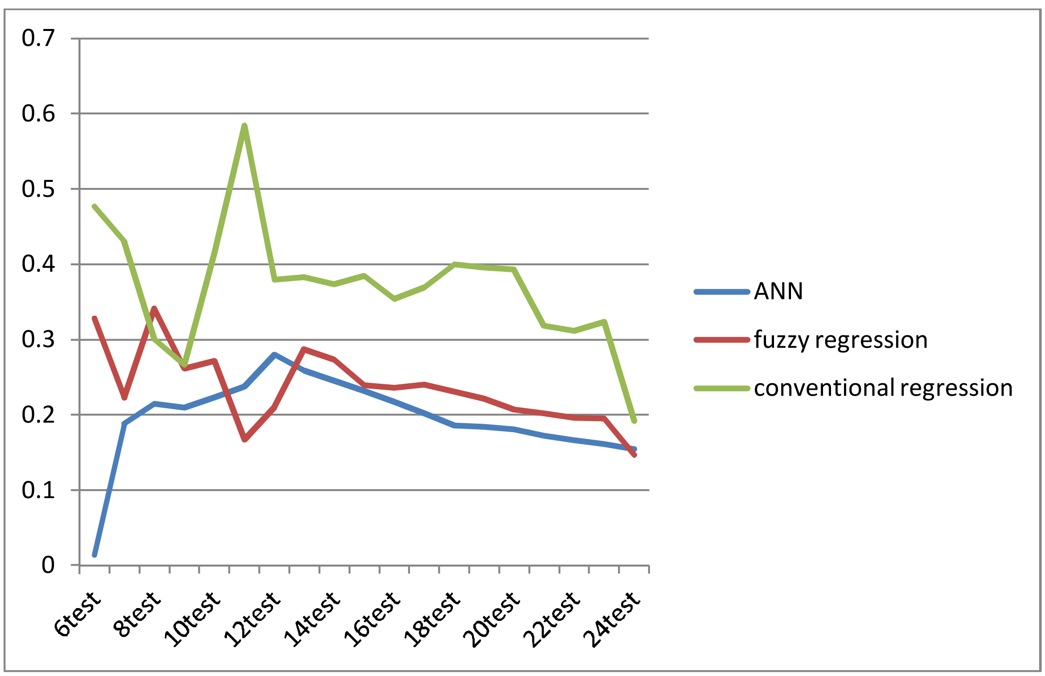

Chart 2. Comparision of neural network, fuzzy regression and conventional regression

7. Conclusion

This research presented an ANN, FR and conventional regression to estimate and predict steel price in Iran. To show the applicability and superiority of the neural network, monthly steel price in Iran from 2008 -2011 were used, trained and tested. The standard indicators used in this study are: exchange rate, export, GDP, import, OPL and oil price. After testing all possible networks with 6,7…23 and 24 rows of unlearned data, we showed that MLP network with trainbfg function had the best output in compare with other function of ANN with its relative error equal to

0.19 on the test data. Afterwards, FR models applied to this data set and its relative error was calculated. Considering the mentioned obtained results of FR models, we can find out the proposed FR models by sakawa and Yano are respectively yielded the best estimation for steel price with its relative error equal to 0.28 on the test data. With compare result of ANN, fuzzy regression and conventional regression it can be seen that neural network get less error than other models.

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References
1. Azadeh A., Ghaderi S.F, Sohrabkhani S., 2006b. Forecasting electrical consumption by neural network. Proceedings of Energex2006: The 11th International Energy Conference and Exibition, Stavanger, Norway, 12-15 June.
2. Azadeh A., Ghaderi S.F., Sohrabkhani S., 2006c. Improving neural networks output with preprocessed data in electricity consumption forecasting. Proceedings of The 36th International Conference on Computers and Industrial Engineering, Taipei, Taiwan, 20-23 June.
3. Azadeh, A., Ghaderi, S.F., Tarverdian, S. and Saberi, M., 2007. Integration of artificial neural networks and genetic algorithm to predict electrical energy consumption. Applied Mathematics & Computations, 186, 1731-1741.
4. Azadeh, A., Saberi, M., Ghaderi, S.F., Gitiforouz,, A. Ebrahimipour, V. 2008a. Improved estimation of electricity demand function by integration of fuzzy system and data mining approach, Energy Conversion and Management, Volume 49, Issue 8, 2165-2177.
5. Beccali M., Cellura M., Lo Brano V., Marvuglia A., 2004. Forecasting daily urban electric load profiles using artificial neural networks. Energy Conversion and Management, 45, 2879–2900.
6. Chow T.W, Leung C. T., 1996. Neural network based short-term load forecasting using weather compensation. IEEE Transactions on Power Systems, 11(4), 1736-1742.
7. Hobbs B.F, Helman U., Jitprapaikulsarn S., Konda S., Maratukulam D., 1998. Artificial neural networks for short-term energy forecasting: Accuracy and economic value. Neurocomputing, 23, 71-84.
8. Hojati, M., Bector, C.R., Smimou, K., 2005, A simple method for computation of fuzzy linear regression, European Journal of Operational Research, 166, 172–184.
9. Hsu C.Ch., Chen Ch.Y., 2003. Regional load forecasting in Taiwan—applications of artificial neural networks. Energy Conversion and Management, 44, 1941–1949.
10. Khotanzad A., Hwang R.C., Abaye A., 1995. An adaptive modular artificial Neural Network hourly load forecaster and its implementation at electric utilities. IEEE Transactions on Power Systems, 10(3), 1716-1722.
11. Khotanzad A., Davis M.H., Abaye A., Maratukulam D.J., 1996. An artificial Neural Network hourly temperature forecaster with applications in load forecasting. IEEE Transactions on Power Systems, 11(2), 870-876.
12. Lai, Y.J., Chang, S.I., 1994, A fuzzy approach for multi-response optimization: An off-line quality engineering problem, Fuzzy Sets and Systems, 63, 117-129.
13. Lee K.Y., Park J.H., 1992. Short-term load forecasting using an artificial neural network. IEEE Transactions on Power Systems, 7(1), 124-130.
14. Mohammed O., Park D., Merchant R., Dinh T., Tong C., Azeem Farah A. et al., 1995. Practical experiences with an adaptive neural network short-term load forecasting system. IEEE Transactions on Power Systems, 10(1), 254-265.
15. Ozelkan, E.C., Duckstein, L., 2000, Multi-objective fuzzy regression: A general framework, Computers and Operations Research, 27, 635–652.

16. Peters, G., 1994, Fuzzy linear regression with fuzzy intervals, Fuzzy Sets and Systems, 63, 45-55.
17. Richardson, P, K, 1998, steel price determination in european community, Journal of Product & Brand Management 7; 62-73.
18. Richardson, P, K, EC, 1999, steel prices and imports: impact of imports from Eastern Europe, Journal of product & Brand Management 8; 443-454.
19. Rumelhart D.E., McClelland J.L., 1986. Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Foundations, MIT Press, Cambridge, MA.
20. Sakawa, M., Yano, H., 1992, Multi-objective fuzzy linear regression analysis for fuzzy input-output data, Fuzzy Sets and Systems, 47, 173-181.
21. Tanaka, H., Hayashi, I., Watada, J., 1989, Possibilistic linear regression analysis for fuzzy data, European Journal of Operational Research, 40, 389-396.
22. Wang, H.F., Tsaur, R.C., 2000, Resolution of fuzzy regression model, European Journal of Operational Research, 126, 637-650.
23. Werbos P.I., 1974, Beyond Regression: new tools for prediction and analysis in the behavior sciences. Ph.D. Thesis, Harvard University, Cambridge, MA.
24. Xia J.,٢٠٠٠, Fundamental Analysis of Price on Chinese Steel Products, Thesis Submitted to College of Business and Economics At West Virginia University.
25. Yalcinoz T., Eminoglu U., 2005. Short term and medium term power distribution load forecasting by Neural Networks. Energy Conversion and Management, 46, 1393- 1405.
26. Yalcinoz T., Eminoglu U., 2005. Short term and medium term power distribution load forecasting by Neural Networks. Energy Conversion and Management, 46, 1393- 1405.
27. Hsu C.Ch., Chen Ch.Y., 2003. Regional load forecasting in Taiwan—applications of artificial neural networks. Energy Conversion and Management, 44, 1941–1949.
28. Beccali M., Cellura M., Lo Brano V., Marvuglia A., 2004. Forecasting daily urban electric load profiles using artificial neural networks. Energy Conversion and Management, 45, 2879–2900.
29. Khotanzad A., Hwang R.C., Abaye A., 1995. An adaptive modular artificial Neural Network hourly load forecaster and its implementation at electric utilities. IEEE Transactions on Power Systems, 10(3), 1716-1722.
30. Khotanzad A., Davis M.H., Abaye A., Maratukulam D.J., 1996. An artificial Neural Network hourly temperature forecaster with applications in load forecasting. IEEE Transactions on Power Systems, 11(2), 870-876.
31. Chow T.W, Leung C. T., 1996. Neural network based short-term load forecasting using weather compensation. IEEE Transactions on Power Systems, 11(4), 1736-1742.
32. Hobbs B.F, Helman U., Jitprapaikulsarn S., Konda S., Maratukulam D., 1998. Artificial neural networks for short-term energy forecasting: Accuracy and economic value. Neurocomputing, 23, 71-84.
33. Lee K.Y., Park J.H., 1992. Short-term load forecasting using an artificial neural network. IEEE Transactions on Power Systems, 7(1), 124-130.
34. Mohammed O., Park D., Merchant R., Dinh T., Tong C., Azeem Farah A. et al., 1995. Practical experiences with an adaptive neural network short-term load forecasting system. IEEE Transactions on Power Systems, 10(1), 254-265.
35. Azadeh A., Ghaderi S.F, Sohrabkhani S., 2006b. Forecasting electrical consumption by neural network. Proceedings of Energex2006: The 11th International Energy Conference and Exibition, Stavanger, Norway, 12-15 June.
36. Azadeh A., Ghaderi S.F., Sohrabkhani S., 2006c. Improving neural networks output with preprocessed data in electricity consumption forecasting. Proceedings of The 36th International Conference on Computers and Industrial Engineering, Taipei, Taiwan, 20-23 June.
37. Azadeh, A., Ghaderi, S.F., Tarverdian, S. and Saberi, M., 2007. Integration of artificial neural networks and genetic algorithm to predict electrical energy consumption. Applied Mathematics & Computations, 186, 1731-1741.
38. Azadeh, A., Saberi, M., Ghaderi, S.F., Gitiforouz,, A. Ebrahimipour, V. 2008a. Improved estimation of electricity demand function by integration of fuzzy system and data mining approach, Energy Conversion and Management, Volume 49, Issue 8, 2165-2177.
39. Wang, H.F., Tsaur, R.C., 2000, Resolution of fuzzy regression model, European Journal of Operational Research, 126, 637-650.
40. Lai, Y.J., Chang, S.I., 1994, A fuzzy approach for multi-response optimization: An off-line quality engineering problem, Fuzzy Sets and Systems, 63, 117-129.
41. Richardson, P, K, 1998, steel price determination in european community, Journal of Product & Brand Management 7; 62-73.
42. Richardson, P, K, EC, 1999, steel prices and imports: impact of imports from Eastern Europe,

Journal of product & Brand Management 8; 443-454.

43. Xia J.,٢٠٠٠, Fundamental Analysis of Price on Chinese Steel Products, Thesis Submitted to College of Business and Economics At West Virginia University.
44. Werbos P.I., 1974, Beyond Regression: new tools for prediction and analysis in the behavior sciences. Ph.D. Thesis, Harvard University, Cambridge, MA.
45. Rumelhart D.E., McClelland J.L., 1986. Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Foundations, MIT Press, Cambridge, MA.
46. Tanaka, H., Hayashi, I., Watada, J., 1989, Possibilistic linear regression analysis for fuzzy data, European Journal of Operational Research, 40, 389-396.
47. Sakawa, M., Yano, H., 1992, Multi-objective fuzzy linear regression analysis for fuzzy input-output data, Fuzzy Sets and Systems, 47, 173-181.
48. Hojati, M., Bector, C.R., Smimou, K., 2005, A simple method for computation of fuzzy linear regression, European Journal of Operational Research, 166, 172–184.
49. Peters, G., 1994, Fuzzy linear regression with fuzzy intervals, Fuzzy Sets and Systems, 63, 45-55.
50. Ozelkan, E.C., Duckstein, L., 2000, Multi-objective fuzzy regression: A general framework, Computers and Operations Research, 27, 635–652.

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